Semantic Web Based Dynamic Energy Analysis and Forecasts in Manufacturing Engineering

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Abstract

This paper proposes an approach for supporting the analysis of collected energy consumption data in combination with structured system models to reveal correlations between energy usage and related properties of products, operations and equipment. The described method serves as a starting point for the creation of tailored simulation models for energy consumption forecasts that can be used in the planning phase of manufacturing systems. Therefore several energy-oriented simulation methods are introduced and discussed regarding their suitability for different use cases in manufacturing engineering.

Keywords:

Energy Efficiency; Linked Data; Simulation

1 INTRODUCTION

Resource efficiency is gaining importance for manufacturers. Rising energy costs and an increasing request for green products demands producers not only to provide energy-saving products, but also to establish energy efficient production processes. This also holds for the automotive industry where more than 20 percent of a car's life-cycle energy usage may arise during its manufacturing process. Hence it is essential to analyze all aspects of energy usage comprehensively for improvement of energy efficiency in manufacturing. Since today's widely used planning tools are unable to predict and optimize energy consumption of planned processes and systems, methods and tools are required that allow for integrated energy forecasts throughout industrial and manufacturing planning.

As a first step towards realizing this vision we propose a method that leverages Semantic Web technologies in order to support analyzes of energy consumption data by linking measured values to descriptions of products, operations and equipment (Section 3). The method can be used to select and filter measurement data for the creation and verification of generalized simulation models that allow predicting energy consumption of different planning alternatives (Section 4).

Our approach is developed and applied within a research project that aims at improving the overall energy efficiency of manufacturing systems for body-in-white parts.

2 STATE OF THE ART

Currently, manufacturing data analysis is mainly applied for resolution of bottlenecks or quality problems. Hence most computer-based analysis systems aim at calculation of performance indicators from process and product data or prediction of process properties for preventive maintenance tasks. More complex evaluations of manufacturing data regarding varying objectives is usually performed with the help of data mining methods and software tools. Data mining requires preprocessing (aggregation, reduction) and manual selection of relevant data sets. The latter becomes increasingly complex with higher amount and diversity of available data. While other domains like biology [1] or meteorology [2] try to find computer-aided solutions for exploration and selection tasks, similar approaches in the field of manufacturing engineering are unknown.

Regarding production planning processes in the automotive sector, advanced tools of the digital factory are used to design work cells and assembly lines. These software systems are mainly evaluating planning solutions regarding time and space requirements. Since the behavior of media consumers often cannot be modeled sufficiently such tools lack support for energy-related decisions.

Furthermore, there are no solutions for using digital planning models to support manufacturing data analysis during the operating stage of planned systems, e.g. by linking collected data to related products, processes and equipment.

3 ANALYSIS AND MODELING OF BODY-IN-WHITE PRODUCTION SYSTEMS

3.1 System Analysis and On-Site Data Acquisition

The reference batch production system is a highly automated assembly line for sheet metal parts which consists of sequential work groups. Almost all process steps are realized by industrial robots. Workers are essentially utilized for placement and removal of parts as well as for quality assurance.

In the current state of technology, joining of sheet metal parts is realized by welding or brazing processes. Within body-in-white applications a welding process is mostly divided into two sequential steps. In a first step the parts are fixed by spot welds. Secondly, the whole weld seams are created. Brazing is used in critical areas for corrosion protection. Both technologies require high process temperatures as well as additional operating media. Beside these core processes, compressed air is of high importance for part handling and clamping.

For this reason, the following media-related values have to be monitored during a defined period of operation:

- Electricity: current, voltage, frequency, effective and apparent power, effective power factor (cos ϕ)
- Coolant water: temperatures (inflow, return flow), volume flow
- Compressed air: pressure, volume flow
- Inert gas: pressure, volume flow

Additionally, temperatures of welding guns and welding fumes are captured. Therefore, measuring devices were installed by automation specialists who are involved in the research project.

As a result, two main data collections are obtained for each media consumer (Figure 1). The first collection contains all media consumption data, the second collection aggregates all operating states of the consumers monitored by their primary controller. Both collections are synchronized by time stamps for each measured value.

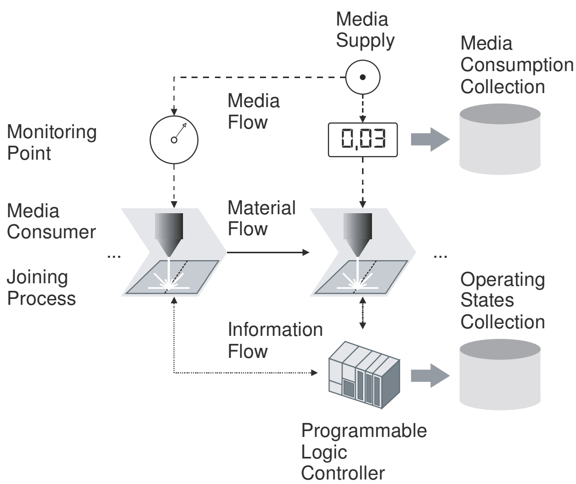

Figure 1 : On-site acquisition of media and process data.

In this way, we aim at deriving correlations between resource states and media consumption. In order to assist the data analysis, our approach uses models for the description of production systems. These models represent structural aspects of the considered system along with behavioral descriptions for the corresponding production processes. These models are intended for guiding and simplifying data exploration tasks like retrieval of media consumption data related to the creation of weld seams or other types of assembly features.

3.2 Ontology-based system models

Advanced modeling techniques are required to cope with the diversity of information about production systems that needs to be integrated for the purpose of guided data analysis.

The Semantic Web as an extension to the World Wide Web enables information sharing across application boundaries and data repositories. Its building blocks are the Resource Description Framework (RDF) [3] enabling unified data representation supplemented by a stack of languages for knowledge modeling using ontologies.

One of these is the Web Ontology Language (OWL) [4] that was widely adopted for ontology definitions in a variety of domains. For example, two extensive research projects COGents and IMPROVE [5] showed that OWL-based ontologies are well-suited to integrate knowledge from different domains into a unified system model. Although these projects considered the engineering of chemical process systems similar concepts can be applied for modeling manufacturing systems. There are also some efforts towards the creation of standardized manufacturing core ontologies, one of these is the *MAnufacturing's Semantics ONtology (MASON)* [6] as proposal for an upper manufacturing ontology.

Our approach uses OWL to define lightweight models of the production systems and the collected data. Hence our ontologies do only specify a small core vocabulary required for data analysis tasks that can be combined with existing manufacturing ontologies like *MASON* to increase the expressiveness.

We've identified three types of elements required to describe the highly automated assembly processes within our reference production system including body-in-white products, operations and equipment.

These concepts are defined in separate ontologies which are related to each other like depicted by Figure 2. The following models are utilized to create a detailed description of our reference system.

Equipment model

The equipment model reflects the hierarchical and topological structure of all relevant body-in-white resources within the reference system. It contains media equipment, e.g. power supplies and distribution equipment, hardware used for process data collection, e.g. monitoring points, as well as all connected media consumers. We distinguish between core processing devices, e.g. robots and welding guns as well as secondary equipment used for tool maintenance, labeling, insertion control, pretreatment and post processing of parts. Furthermore, different cylinders, feeders as well as disposal and safety devices are represented.

Product Model

This model focuses closure parts, particularly a rear door produced by the reference production system. The hierarchical structure of sub-assemblies and individual parts are modeled as well as important attributes like materials, weights, sheet thicknesses, potential clamping points and joints.

Operations Model

All steps performed during production including processing, transportation, handling and storage are contained in that model. Beside core processes, we consider security-related operations as well as jig-related operations. Operations are linked to the utilized equipment and modified parts (Figure 1).

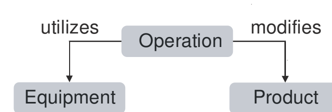

Figure 2 : Relationships between models.

3.3 Semantic Data Representation

Large scale data analysis requires deep insight into the systems and processes that produced the data under consideration. Especially in the case of production systems, an analyst has to cope with complex structures of products, operations and equipment. Hence, the analysis of collected production data is often time-consuming and error-prone.

We try to solve this problem by introducing an approach for guided data exploration of production data. Our method is based on the idea of linking sensor descriptions and collected sensor data to models of products, operations and equipment.

Recent research concentrates on publishing and analyzing sensor data using Semantic Web technologies. There are ongoing efforts to describe the topology of sensor networks with ontologies [7] along with complementary investigations for linking collected sensor data with sensor network models to simplify retrieval and analysis tasks [2].

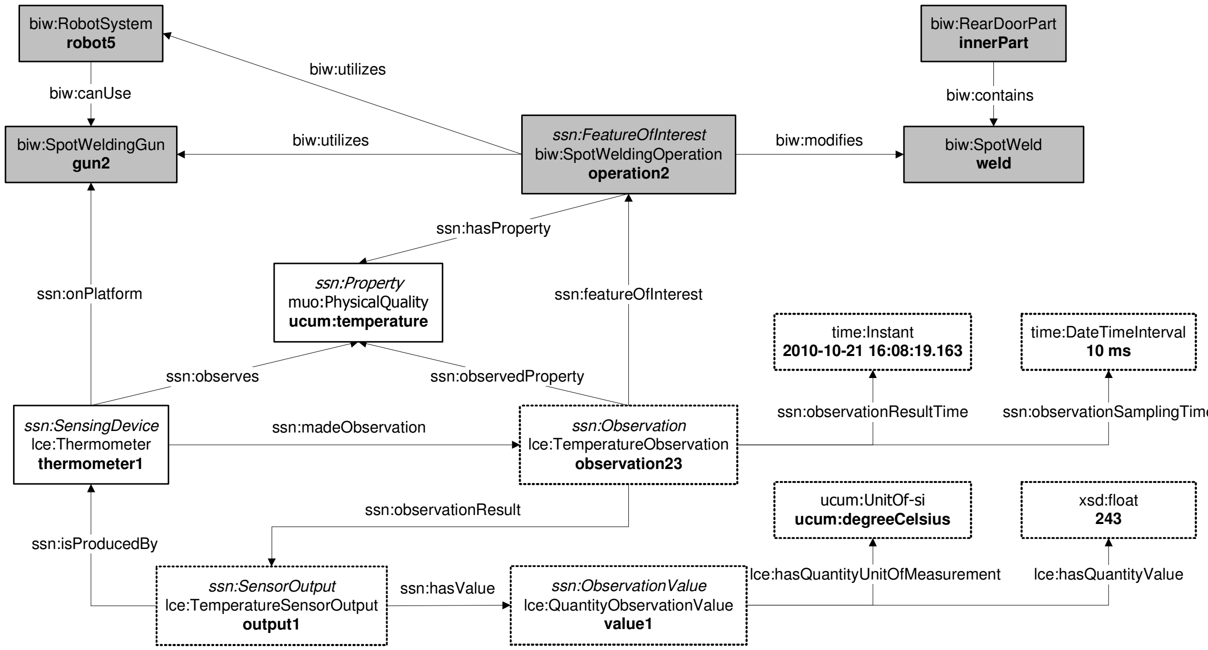

Figure 3 : Collected sensor data linked to operation, equipment and product.

The W3C Semantic Sensor Networks Incubator Group (SSN-XG) aims to build a unified ontology for sensors and collected sensor data. The resulting *Semantic Sensor Network (SSN) Ontology* provides means to describe sensors, observations and related concepts. It is targeted at a wide range of applications and hence has a very general nature that is achieved by omitting descriptions for domain concepts like time, locations and others. These can be added for different use cases by utilizing OWL's import facility.

Figure 3 illustrates an example that shows how sensor data, in this case temperature data, expressed in the SSN ontology can be linked to the data-producing process.

The SSN ontology speaks about *SensingDevices* that make *Observations* regarding *Properties* of a *FeatureOfInterest*. In our example the sensing device is a thermometer that observes the temperature of a spot welding operation. The sampling time of these temperature observations is fixed to *10ms,* meaning that the *ObservationValue* of the associated *SensorOuput* is regarded valid for this duration.

The connection between collected sensor data and the production system model is established by using manufacturing operations as features of interest for observations. The example in Figure 3 illustrates this by connecting the temperature observation to a concrete instance of *SpotWeldingOperation*. This allows for further traversal of associated model elements like modified parts and utilized equipment.

Since the SSN ontology does not define concepts for representing time and other physical quantities it has to be supplemented by other ontologies for this purpose.

We've decided to use the widely accepted OWL-Time ontology [8] to represent temporal concepts like observation result time and sampling time.

Physical qualities and associated units are represented using the *Measurement Units Ontology (MUO)*. MUO provides a formal framework for defining base units and their derived forms. There exists a set of basic instances for MUO that was extracted from UCUM, the *Unified Code for Units of Measure*. This UCUM ontology was reused to express physical units like °C (ucum:degreeCelsius) in an unambiguous way.

3.4 Guided Data Exploration

The semantic linking of sensor data with model elements supports the analyst in exploring and examining the collected data to identify relevant energy-usage patterns.

The starting point is a graphical representation of the production system that reflects its hierarchical and topological structure along with attached sensing devices. The general idea is to use an equipment object as source for observations regarding properties of its state or properties of its associated manufacturing operations.

Figure 4 exemplifies the visualization of observed property values for a robot system. The view can be generated by leveraging the semantics of the ontology-based production system model. The integrated retrieval of model and measurement data is realized by using SPARQL [9] (*SPARQL Protocol and RDF Query Language*) which is part of the W3C Semantic Web stack and provides tailored querying facilities to access RDF-based data.

The following SPARQL query retrieves manufacturing operations or operating states along with their observed properties for a given equipment object.

```
PREFIX biw:<http://iwu.fraunhofer.de/manufacturing/biw#>
PREFIX ssn:<http://purl.oclc.org/NET/ssnx/ssn#>

SELECT DISTINCT ?foi ?property WHERE {
        # feature of interest is either an operation or a
        # system state
        {?foi biw:utilizes ?equipment} UNION
        {?foi biw:possibleStateOf ?equipment}
        ?foi ssn:hasProperty ?property .
        ?property a ssn:Property .
        # there is at least one observation for this property
        ?observation a ssn:Observation .
        ?observation ssn:featureOfInterest ?foi .
        ?observation ssn:observedProperty ?property
}
```

Based on the results of this query it is possible to construct an analysis view composed of diagrams for each observed property as depicted by Figure 4. As can be seen, the observed properties in this example are *temperature* and *power consumption*. Complementary to the diagrams for property values, a timeline is available to visualize the active intervals of manufacturing operations or system states. Additional properties of these objects (like actual system state or modified parts) can selectively be retrieved and visualized for a deeper understanding of the observation results.

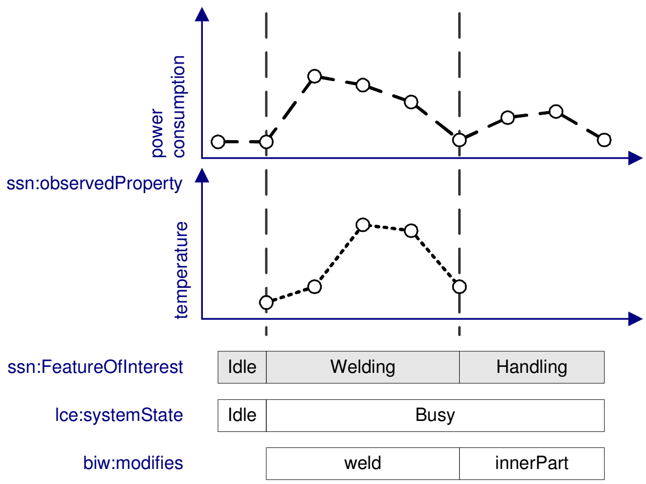

Figure 4 : Visualization of observed property values

Exemplary, the actual values for each property can be queried by the following SPARQL query:

```
PREFIX dul:<http://www.loa-cnr.it/ontologies/DUL.owl#>
PREFIX time:<http://www.w3.org/2006/time#>
PREFIX ssn:<http://purl.oclc.org/NET/ssnx/ssn#>
PREFIX xsd:<http://www.w3.org/2001/XMLSchema#>

SELECT ?value ?rtime WHERE {
  ?o a ssn:Observation .
  ?o ssn:observedProperty ?property .
  ?o ssn:featureOfInterest ?foi .
  ?o ssn:observationResultTime [
       time:inXSDDateTime ?rtime
  ] .
  ?o ssn:observationResult [
       ssn:hasValue [dul:hasRegionDataValue ?value]
  ] .
  FILTER (?rtime > ?startTime && ?rtime < ?endTime)
}
```

This query takes a given feature of interest (foi), a property of this feature of interest (property) and the bounds of a time interval (startTime, endTime) as input. The results are pairs of scalar property values and corresponding event times determined by observations within the given time interval.

We term the described method guided data exploration since it enables combination of knowledge about the structure and behavior of the production system with knowledge about process observations helping the analyst to navigate and interpret large sets of collected process data.

3.5 Verification of energy-oriented simulation models

Section 4 introduces a method for energy consumption forecasts using simulation. The verification of constructed simulation models requires sample data which was produced by real world systems. Our proposed approach to data exploration can support the iterative creation, verification and modification of energy-oriented simulation models for manufacturing processes. The described linking of collected process data with products, operations and equipment aids the analyst to retrieve the measured energy consumption data required for comparison with simulation results.

4 SIMULATION-BASED MEDIA/ENERGY (CONSUMPTION) FORECASTS

Obviously, on-site measurements of energy consumption as foundation for energy usage predictions are only applicable for constant conditions, e.g. fixed system configurations. Such measurements cause high investment costs and temporary shutdowns of production for installations. For virtually planned systems they can not be used at all.

In these cases, simulation tools may be applied. A rough distinction is drawn between discrete and continuous simulation. In contrast to continuous simulation, the value of a state variable is not recalculated and can not be accessed at any time within discrete simulation [10]. On the other hand, material flow-related aspects can be modeled more easily for piece goods.

Discrete event simulations are well-established within production planning. As energy consumption can not be a single objective for optimization, other important facts [11], e.g. cycle time, utilization and output ratio of the system have to be evaluated in advance using such systems.

Continuous simulations are mainly used for process modeling, e.g. process engineering or for product development, e.g. design and engineering of mechatronic systems.

In order to predict energy consumption for a system of resources using simulation, we distinguish different realization options:

1. Complete representation of the production system including all resources within continuous simulation (cp. [12]).
2. Online coupling of discrete simulation of the production system and continuous simulation of resources (cp. [13, 14]).
3. Successive discrete and continuous runs tracing events from log file.

In the following part, we demonstrate two approaches for energy consumption forecasts within common continuous and discrete simulation systems.

4.1 Physical Modeling of Energy Consuming Resources

This approach requires knowledge about the structure and the physical behavior of the resource. For example, our Modelica model [15] of a simplified robot consists of several sub-models (Figure 5).

Structural model

This model of the robot structure contains a path planning component generating required kinematic movement angles, a controls bus, body shapes, a world coordinate system, revolute joints and an axis model.

Axis model

This sub model of a driven axis comprises a proportional-integral axis controller, an axis control bus, a gearbox, different sensors, a signal generator and a drive model.

Drive model

The structure of the motor is made up of different sensors, electrical and electronical components as well as a rotational component with inertia and an electromotoric force by means of an electric/mechanic transformer. Furthermore, the electromotoric force block is linked with a power sensor and an integrator block in order to add up its energy consumption during a simulation run.

We used a fictional operation as input for the path planning block. For a vertical circular rotation of a defined mass by 180 degrees, we obtained an energy profile as shown in Figure 5. The negative integration values in the upper region are caused by recovery of braking energy.

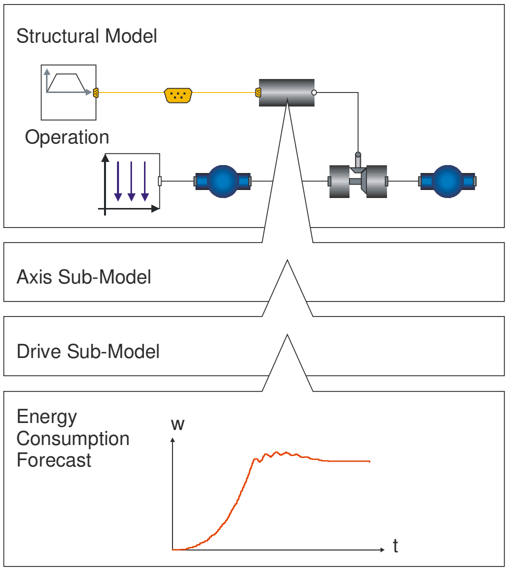

Figure 5 : Hierarchical simulation model of a simplified robot.

4.2 State-based Simulation Models of Energy Consuming Resources

This approach implements time-dependent state variables, e.g. effective power, using an object-oriented discrete-event simulation system.

Each resource is regarded as a finite state machine that contains several distinct states. Considering simple material flow resources, these distinct states may consist of *Working*, *Set-up*, *Failure*, *Pausing*, *Blocking*, *Waiting* resp. *Empty* and *Non-planned*. An individual state of a resource is modeled by using a representative material flow object that is characterized by one or more state variables.

Each state variable is described by a predetermined time-dependent value function that can, for example, be computed by continuous simulation runs.

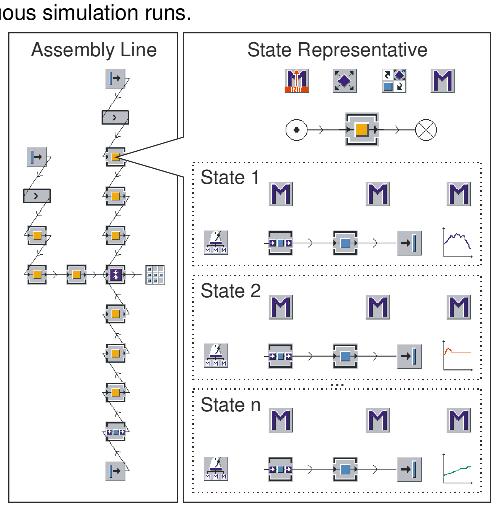

Figure 6 : Resource network for modeling state variables.

The characteristic value function of each state variable is discretized [16] to enable the integration into a discrete-event simulation model. Within the discrete-event simulation individual value functions can then be represented by combining simple time-value lookup tables for each state variable with an event generator that triggers the required value changes at the right time.

State changes of resources are modeled by activating corresponding representative flow objects for each state (Figure 6).

In that way, the characteristic behavior of state variables, e.g. effective power, for individual resource states can be simulated using discrete-event simulation systems.

The following simplifications were applied for the example shown in Figure 7:

- Values of state variables solely depend on the elapsed time within the corresponding state.
- The elapsed time of a state is not reset if it is interrupted by an exceptional state, e.g. when processing is interrupted by maintenance. This is based on the assumption that the original activity can be continued and does not require restarting.
- The states *Waiting/Empty*, *Blocking*, *Pausing* and *Non-planned* are merged into a state called *Other*.

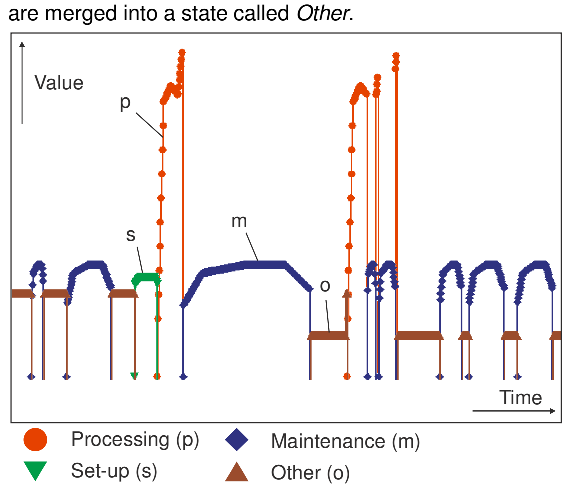

Figure 7 : Simulated development of state value within different states of the main resource.

For illustration purposes, the resource has a low availability ratio requiring some maintenance states while processing. It is also part of an unbalanced line where blocking and waiting states can occur.

The described method enables modeling complex material flow systems while also considering characteristics of state variables like power consumption.

A resource's energy consumption *w* within can for example be approximated by Equation 1 where *n* is the number of events that triggered changes of the effective power p_i. The value of p_i is considered constant within the interval Δt_i. Better approximations are possible by using some kind of interpolation.

$$w = \sum_{i=1}^{n} p_i \cdot \Delta t_i \qquad (1)$$

This method enables the determination of energy consumption-related characteristics for evaluating different planning solutions. Therefore, it provides the basis for further optimizations.

5 OUTLOOK: INTEGRATION INTO PROCESS PLANNING (CAPP)

An integration of energy-related objectives into body-in-white planning processes is necessary to obtain energy efficient solutions.

In a first step, energy-related objectives must be developed, e.g. reduction of lines' energy consumption by 25% while retaining equal throughput and product quality. As it is hard to numerically qualify such targets in the beginning, a maximum decrease of energy consumption in conformance with main planning objectives like time, quality and costs would be a more generic approach. Since energy suppliers are usually aggregating consumed power over a certain period of time for accounting, consumption rhythm and load peaks may form additional important objectives.

Secondly, different solutions are developed leveraging common planning and engineering tools. For body-in-white processes, collision tests and accessibilities relating to robots, tools, jigs, parts and other equipment are of great importance. Currently, all processes are optimized to duration and space requirements. This influences the formation of work cells, as cycle times determined from process simulation have to be balanced in order to reduce the cycle time of the whole line. Iterative planning helps to evaluate and optimize different solutions concerning planning objectives defined in advance.

The second step lacks support for energy-related decision, since current tools are unable to support congruent determination of energy consumption, temporal and spatial objectives within process simulation. Thus, planning solutions are tested for energy-related objectives by leveraging simulation as described in section 4. In order to reduce iteration loops, an integration of energetic aspects into process planning tools would be worthwhile. Automatic approaches like introduced in [17] can be a starting point for energy-sensitive planning by using integrated optimization techniques.

6 SUMMARY

This paper presented a Semantic Web-based approach to manufacturing data analysis regarding energy consumption and accompanying generalization of findings by simulation models for dynamic energy forecasts during the planning phase.

We showed that the application of ontologies for production system descriptions enables their combination with collected product and process data. Based on this technology, an approach for guided data exploration was introduced that supports the selection of relevant data sets in manufacturing data analysis. Furthermore, it can be used to compile relevant data for the verification of simulation models.

Regarding such simulation models, several methods were introduced that enable the consideration of energy efficiency for planning purposes.

7 ACKNOWLEDGMENTS

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